# Optimal Charging Schedule of Electric Vehicles at Battery Swapping Stations in a Smart Distribution Network

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*Abstract*— **Motivated by indispensable requirements of large penetration of electric vehicles (EVs), battery swapping is an efficient performance to exert benefits of changing batteries within a short time period and charging them during off-peak hours. This paper proposes a strategy trying to find the best charging procedure of electric vehicles in an environment toward battery swapping stations (BSSs). The goal of the strategy is to minimize the charging cost as well as to reduce energy loss. Voltage deviation of buses, power flow of network branches, and maximum power consumption of BSSs are considered as constraints of this optimization problem. In order to solve the issue, a population-based evolutionary approach, which is a modified hybrid form of genetic algorithm (GA) and particle swarm optimization (PSO) algorithm, is employed. The strategy is implemented on IEEE 33-bus distribution network test system and numerical results are illustrated.**

Keywords—**Electric vehicle, battery swapping station, charging strategy, modified GA-PSO algorithm.**

## NOMENCLATURE

| | |
|---|---|
| $T$ | Number of time slots in charging period |
| $\delta$ | Time span of each time slot |
| $Nb$ | Total number of buses in the network |
| $nb$ | Total Number of Branches in the network |
| $N$ | Total number of BSSs |
| $m$ | Number of EVs in each group |
| $D$ | Total Number of EVs group |
| $W_{it}$ | Decision variables vector at iteration $it$ |
| $x_{n,it}$ | Charging priority of group n at iteration $it$ |
| $y_{n,it}$ | Charging location of group n at iteration $it$ |
| $z$ | Objective function of the problem |
| $z^{M}$ | Modified objective function of the problem |
| $PVC_{i,t}$ | Penalty of voltage constraint of bus $i$ at time slot $t$ |
| $PAPC_b$ | Penalty of apparent power constraint of branch $b$ among all time slots |
| $TPVC$ | Total penalty of voltage constraint |
| $TPAPC$ | Total penalty of apparent power constraint |
| $\alpha_V, \alpha_S$ | Penalty coefficients of voltage and apparent power constraints, respectively |
| $Pri_t$ | Electricity Price at time slot $t$ |
| $R_b$ | Resistance of branch $b$ |
| $I_{b,t}$ | Current of branch $b$ at time slot $t$ |
| $V_{i,t}$ | Voltage magnitude of bus $i$ at time slot $t$ |
| $V_i^{Max}$ | Maximum permissible voltage magnitude of bus $i$ |
| $V_i^{Min}$ | Minimum permissible voltage magnitude of bus $i$ |
| $P_t$ | Power demand of BSSs and power loss at time slot $t$ |
| $P_t^{Ch}$ | Power demand of BSSs at time slot $t$ |
| $P_{k,t}^{BSS}$ | Power demand of BSS $k$ at time slot $t$ |
| $P_t^{Loss}$ | Power loss of the system at time slot $t$ |
| $P_t^{Max}$ | Regulated maximum total power consumption of the system at time slot $t$ |
| $P_t^{Load}$ | Residential power consumption at time slot $t$ |
| $P_t^{Rem}$ | Remained Power available for EVs Charging at time slot $t$ |
| $S_{b,t}$ | Apparent power flowing through branch $b$ at time slot $t$ |
| $S_b$ | Maximum apparent power flowing through branch $b$ among all time slots |
| $S_b^{Max}$ | Maximum permissible apparent power flowing through branch $b$ |
| $S_k^{BSS}$ | Apparent power flowing through the branch ending with the bus connected to BSS $k$ among all time slots |
| $S_k^{BSS,Max}$ | Regulated maximum apparent power flowing through the branch ending with the BSS $k$ |

## I. INTRODUCTION

With the rapid growth of population and use of fossil fuels in the last decades, the global society has faced to problems including air pollution, greenhouse effect, fuel price increase, and depletion of fossil fuel resources. In order to mitigate such issues, deploying electric vehicles together with renewable generations (RGs) in large scales has been considered as a promising solution [1]. In some cases, the promotion of governments has caused the rapid growth of EVs just as it came to pass in China as a specimen [2]. Along with the presence of vehicles run by direct connection to the electrical network while moving, like electric trains and some electric buses, several technologies have been defined so far to provide the energy of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) such as slow charging, fast charging, battery swapping, and wireless charging [3, 4].

According to the joint nodes of transportation and power system created by EVs and charging stations [4], the two systems can interact deeply on each other. Despite the advantages of EVs, whether in terms of economic or environmental aspects, large utilization of these vehicles with uncertainty of charging behaviors can cause power system to operate under unwanted inefficient circumstances [5, 6]. The operation of a power system can face problems in some of its factors such as loading and voltage profile [5], difference between peak and off-peak loads [6], loading amount of network branches, and energy loss (caused by current flowing through branches) without an efficient scheduling of EVs connections to the distribution network. It is possible even in some conditions that these problems threaten the reliability and security of the system. On the other hand, constraints of the power system can interfere with the comfort of vehicle drivers [6]. Thus, there should be a coherent management for this type of transportation fleet to not only keep away from such problems but also utilize the storage feature and dispersed removable loads property of EVs [7] with the presence of smart grid infrastructure and thereby, enhance the reliability [1], flexibility and power quality of the electrical system.

In order to attract people to choose EVs and make the penetration extent of EVs larger, considerable efforts have been made by researchers to solve the difficulties existing on the way. To reduce the charging time of EVs' batteries approaching to refueling time duration of gasoline-based vehicles (e.g. about 90 seconds for Tesla battery swapping service [4]) and to mitigate the charging control procedures' burden on the drivers along with preserving the power distribution system work properly, battery swapping scenario has been defined [8]. In fact, an EV driver will receive a fully-charged battery instead of his/her flat battery by paying the different state of charge (SoC) of the two batteries in a BSS. Flat batteries are gathered in the BSSs and are charged at a time considered to be suitable. Thus, BSSs can participate in the wholesale electrical market to buy cheaper energy or can manage to buy it from renewable RGs. They can even provide profitable ancillary services, on the other hand [4]. So, if the regulations of standardization and commercialization associated with this type of stations will be well established and also the optimal charging procedures of the batteries will be introduced, this charging strategy of EVs can be promising.

In recent years, considerable endeavors have been focused on the battery swapping strategy. A comparison between the planning of two types of stations based on life cycle cost was done by [8] in which there was shown that the BSS is more appropriate for public transportation system than rapid charging stations. In [9], random behavior of a BSS was taken into account and thereby, a stochastic modeling based on Monte Carlo simulation is deployed to predict the consumption of the BSS for alleviating the impact of charging behavior. A business modeling of day-ahead charging scheduling considering the uncertain demand for battery swapping along with the modeling of electricity price uncertainty was accomplished by [10]. Optimized operation of EVs and BSSs under uncoordinated charging pattern in a relatively smaller area like a microgrid is discussed in [11]. Reliability assessment of distribution system with BSSs is taken into account by [7, 12]; The behavior of EV users is modeled in these studies and the results show that the reliability performance of the system can be enhanced by the presence of BSSs.

In this paper, an optimal charging of EVs under the battery swapping procedure in BSSs are designed. Charging location and priority of the EVs are considered as decision variables of the optimization problem. A modified hybrid GA-PSO algorithm is employed to update the variables in the solution space in order to approach to the best solution. A mathematical algorithm was defined using the variables produced by the evolutionary algorithm in order to find the deterministic least possible cost of charging along with energy loss. Limitations of voltage fluctuations, bounds of apparent power flowing within the branches of the electrical network, and the maximum permissible power consumption of each BSS are considered as the constraints of the optimization problem. It is assumed that the infrastructure is implemented within a smart grid. So, the variable pricing scheme of electricity, a function of the power consumption of the whole system, is considered. The backward-forward power flow (BFPF) is deployed and the strategy is implemented on IEEE 33-bus radial test system.

## II. Problem Definition

Due to the energy absorbed by BSSs, there should be a coherent charging schedule of batteries in order not to face to unsuitable operation of the power system from technical and economical points of view which can be occurred by stochastic charging procedures of large amounts of EVs. We supposed that the distribution system divided into some smaller area in which the BSSs are located and each area is controlled by an aggregator. The extent of each area is not as large as to one which make an EV user drive much from one place to another. The aggregator is also responsible for the energy loss of its area. So, the goal of the problem is to find the least possible charging and energy loss by considering not to disturb the stability and security of the system's operation. It is considered that the reactive power requirements of each BSS provided by itself. In fact, the BSSs don't absorb reactive power from the grid. It is supposed that the system operates in a smart grid infrastructure with the potential of using internet of things (IoT). Each time an EV requests the aggregator to determine a BSS for battery swapping, it is possible to the aggregator to specify the location due to SoC of that vehicle along with the scheduling program run before. Furthermore, the distribution system has the ability to change the price of electricity in relation to the power consumed. All of these can be fulfilled by IoT technology in a smart grid infrastructure of the distribution system. It is supposed also, for each particular type of batteries, the cost of battery swapping will be constant for any level of SoC.

### A. Decision Variables

To find the optimal charging schedule of EVs, priority and location of charging are considered as decision variables. By changing the two type of variables, we search the best possible work point of the problem.

### B. Objective Function

As stated before, the objective of the optimization problem comprises the minimization of charging cost of the whole EVs will be charged in a particular area and the energy loss of the considered area within a day and night. So, we have the following equation:

$$z = \min\left\{\sum_{t=1}^{T} P_t.\delta.Pri_t\right\} \tag{1}$$

where in:

$$P_t = P_t^{\text{Ch}} + P_t^{\text{Loss}} \tag{2}$$

$$P_t^{\text{Ch}} = \sum_{k=1}^{N} P_{k,t}^{\text{BSS}} \tag{3}$$

$$P_t^{\text{Loss}} = \sum_{b=1}^{nb} R_b.|I_{b,t}|^2 \tag{4}$$

### C. Constraints

The constraints of the problem include the operational stability of the bus voltages, the limitation for apparent power flowing within each branches, and the maximum permissible power consumption for each BSS (in order to control the power consumption of them); The latter one allows us to control the number of EVs coming to each BSS of the area for battery swapping; This action is done due to the fact that the BSSs are planned to be distributed throughout the area in order to receive almost the same customers, and by this constraint, we actually want to simulate the non-electric constraints to an electric constraint. The constraints are formulated as follows:

$$V_i^{\text{Min}} \le V_{i,t} \le V_i^{\text{Max}} \quad , \quad \begin{array}{l}\forall i \in \{1,2,...,Nb\} \\ \forall t \in \{1,2,...,T\}\end{array} \tag{5}$$

$$S_b \le S_b^{\text{Max}} \qquad \forall b \in \{1,2,...,nb\} \tag{6a}$$

$$S_b = \max\{S_{b,1}, S_{b,2}, ..., S_{b,T}\} \tag{6b}$$

$$S_k^{\text{BSS}} \le S_k^{\text{BSS,Max}} \tag{7}$$

The third constraint (7) effects just as the second one (6a) does. As the constraints aren't applied on the decision variables of the optimization problem, they are presented as penalty functions in the objective function of the problem. So the two following ($TPVC$ and $TPAPC$) are added to the equation (1):

$$\begin{aligned} PVC_{i,t} &= \left[\max(V_{i,t}, V_i^{\text{Max}}) - V_i^{\text{Max}}\right] \\ &\quad + \left[V_i^{\text{Min}} - \min(V_{i,t}, V_i^{\text{Min}})\right] \end{aligned} \tag{8}$$

$$\begin{aligned} PAPC_b &= \left\{\left[\max(S_b, S_b^{\text{Max}}) - S_b^{\text{Max}}\right] + \left[-S_b^{\text{Max}} - \right.\right. \\ &\left.\left.\min(S_b, -S_b^{\text{Max}})\right]\right\} + \left\{\left[\max(S_k^{\text{BSS}}, S_k^{\text{BSS,Max}}) - \right.\right. \\ &\left.\left. S_k^{\text{BSS,Max}}\right] + \left[-S_k^{\text{BSS,Max}} + \min(S_k^{\text{BSS}}, -S_k^{\text{BSS,Max}})\right]\right. \end{aligned} \tag{9}$$

$$TPVC = \sum_{i=1}^{Nb}\sum_{t=1}^{T} PVC_{i,t} \tag{10}$$

$$TPAPC = \sum_{i=1}^{nb} PAPC_b \tag{11}$$

The objective function is modified as:

$$z^{\text{M}} = \min\left\{\left(\sum_{t=1}^{T} P_t.\delta.Pri_t\right) + \alpha_V.TPVC + \alpha_S.TPAPC\right\} \tag{12}$$

The two penalty coefficients are assumed to be too big values like $10^{20}$.

## III. Evolutionary Algorithm

Since some parts of the program can't be defined exactly before happening and they are required to be predicted such as residential load curve and the SoC of EVs' batteries, it is acceptable to solve this large-size non-convex and nonlinear optimization problem by using evolutionary algorithms to find the best answer in a solution set. The population-based evolutionary algorithm used to update the values of decision variables, is a modified hybrid version of the two algorithms GA and PSO [6]. Indeed, we use the evolutionary algorithm to find the best priorities and locations for EVs in which their batteries to be swapped. Both of the two types of decision variables are extent to the number of EV groups in the area. Therefore, the decision variables vector generated by iteration $it$ is defined by:

$$W_{it} = \left[x_{1,it}, x_{2,it}, ..., x_{D,it}, y_{1,it}, y_{2,it}, ..., y_{D,it}\right] \tag{13}$$

which the first D variables denote to the charging priority of the EV groups and the second D ones are the charging locations (location of BSSs) of the EV groups.

## IV. Electric Vehicle Charging Rule

Each time the decision variables are updated, the information of the variables along with the SoC of EV groups will be used by the electric vehicle charging rule (EVCR) program to determine the charging time period of each EV group among the whole time slots together with the values of power consumption of each BSS. Indeed, the program deterministically define the least possible cost of charging period for each EV group according to SoC, charging priority and location dedicated for that group. It is noticeable that no interruption will occur within the charging period of each group with this day-ahead charging strategy. For each time the program raises the value of power consumption in a specific time slot, the whole power consumed until then is checked in order to raise a step in price value if the total power increased up to a predefined value. In fact, the program react smartly to the rise of electricity price in a smart distribution network. It is necessary to mention that after the program is run, it should be checked that whether the total batteries were fully charged or not; if the answer is no, there was not enough space for charging the whole batteries and we should change a parameter or parameters to solve the problem; the parameters can be the number of EVs dedicated for each group (and therefore followed by the number of groups –in order to hold the number of total EVs constant), the total number of EVs to be charged, maximum permissible value of power consumption for the whole system, and so on. The maximum permissible amount of active power in each time slot that the BSSs can consume is defined as:

$$P_t^{\mathrm{Rem}} = P_t^{\mathrm{Max}} - P_t^{\mathrm{Load}} \tag{14}$$

$$P_t^{\mathrm{Ch}} \le P_t^{\mathrm{Rem}} \tag{15}$$

## V. Power Flow

Instead of regulating the set point of generators across a network with constant loads in a conventional optimal power flow (OPF) problem, we regulate the value of loads (i.e. the power consumption of BSSs) by dispatching the load flow of EVs charging to gain the optimal set point of network loading, instead. Indeed, it can be considered that each BSS has a constant load and connects to a source of power (generator) simultaneously, which changes the total power consumption of BSS-generator set. Thereby, we are actually solving an OPF or optimal load flow problem as a whole sight.

Due to the fact that we use a radial distribution network, we cannot use conventional power flow solving methods like Newton-Raphson according to its complexity in these networks. Likewise, instead of using the power flow equations, we use backward-forward power flow (BFPF) method [13] which is suitable for radial networks. Every time the decision variables are updated, followed by defining power consumption values of BSSs by EVCR, we acquire the values of bus voltages and branch currents of the network by using BFPF which can also specify the value of power loss and the total active and reactive power obtained from the substation (or slack bus). With climaxing to this point, we are ready to evaluate the objective function and constraints which were defined before, then comparing the result with the best one among all previous results in the evolutionary algorithm to determine and hold the best answer until now.

## VI. Case Study

In order to validate the proposed strategy, the charging schedule algorithm was implemented on a case study which we introduce its details in the following parts:

### A. Final Assumptions and Settings

Some final assumptions and settings used to accommodate the case study to our problem are:

*1)* It is assumed that the batteries of EVs will charge in the form of groups, i.e. the unit of charging loads is a group of batteries not a single battery in order to predict the amount of energy for each unit more accurate. Indeed, despite the strategy can be run by a single EV as a unit of load, but the prediction process needs field study and probabilistic analysis in this case. Likewise, it is supposed that the models of EVs in each group are same to each other.

*2)* Although it doesn't make difference to solve the problem with different numbers and types of EVs through EV groups, it is presumed that all groups have the same number and type of EVs for simplification. The number of EVs in each group (m) was considered 10 with the total number of EVs 1000 (so we have 100 groups) for the total charging period within a day and night in the region. EV-Tesla Model S (released in 2014) [14] was chosen as the type of EVs. Capacity of batteries is 85 kWh with charge efficiency of 92%. We suppose that BSS operators won't accept battery swapping for batteries whose SoC values are less than 15% and up to 70%. The first one refers to the low operating quality of voltage which hinder the driver to ride any longer and the latter refers to adhere to the battery life duration.

*3)* There are two kinds of chargers: 10 kW (slow charging) and 20 kW (fast charging). At the beginning of the charging process of each group, it is assumed to use slow charging pattern for all EVs. So, the total power consumption of each group will be 10m kWh. As soon as each EV in an EV group is fully charged, another EV in that group, which is under slow charging pattern and is not charged fully yet, will has its charging process changed from slow to fast charging pattern. Thereby a group consumes 10m kWh in almost all moments of its charging period [6].

*4)* The price of battery swapping is considered to be the same for each amount of SoC each EV has. By this procedure the batteries intended to be swapped will tend to its lower amounts of SoC which is more beneficial for the battery life. Furthermore, the prediction process of SoC will be more accurate. To generate the amounts of time slots that the EV groups need to be fully charged, we use beta distribution function with the maximum and minimum of 70 and 15 percent (refers to the possible SoC of batteries in time of swapping), respectively with the maximum occurrence possibility of 25.76 percent.

*5)* The active power demand curve of residential loads that is used in this paper is depicted in Fig. 1 [6].

*6)* We use spot pricing scheme exploited from New York Independent System Operator (NYISO) that is based on July 16, 2013 [18]. It is demonstrated in Fig. 2.

*7)* It is explicit to be better to charge the batteries gathered in each BSS during off-peak time periods (e.g. night time) for the usual least amount of residential power demand, therefore low electricity price and depleted capacity of network branches; Nevertheless, it should be considered that by charging batteries in these periods, the valleys of load curve will be filling gradually, triggering probably more costly generators to operate and thus the energy price will rise.

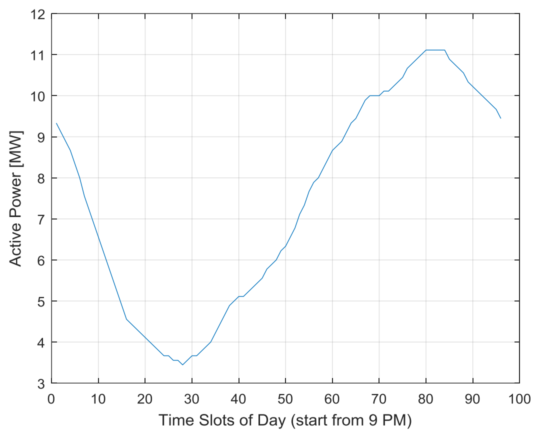


Fig. 1. Total Daily residential Power Consumption of the System

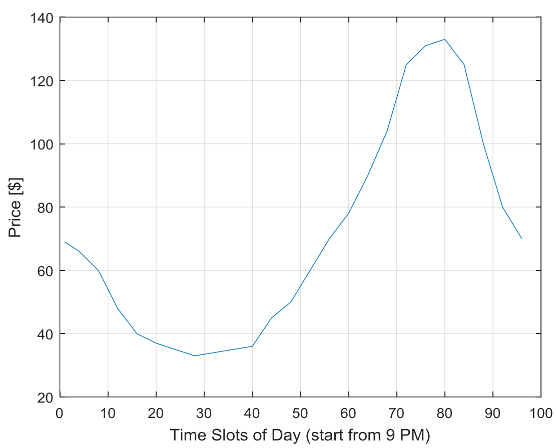


Fig. 2. Fundamental Electricity price of the system

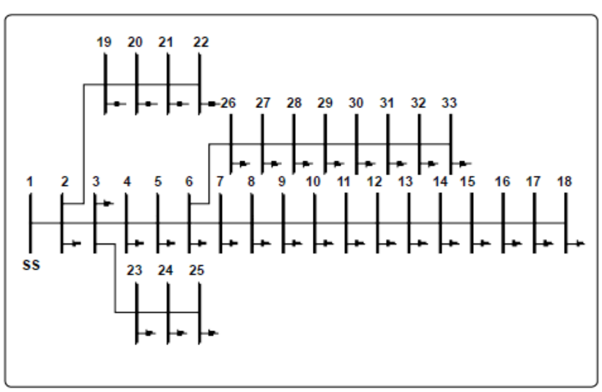


Fig. 3. Single diagram of IEEE 33-bus test system Configurations

In order to simulate the practical condition and impede creating any new peak load, it is assumed that the Price will almost change by changing the amount of power. In this case, the price will rise for 6.5$ when the active power ascends more than 0.5 MW. Thus, we exert a real-time pricing for charging EVs. In practice, the electrical distribution agencies may want to follow another procedure to raise the price or even the aggregator of BSSs may participate in wholesale market, at all.

### B. Electrical Distribution Network

A modified form of IEEE 33-bus test system is considered as the case study of distribution system. The configuration of the network is illustrated in Fig. 3 [15-17]. In order to consider EVs used in practical applications with real battery capacities, we needs up-to-date information of distribution system. Therefore, we assumed that the active power demand of the whole system is raised from 3.715 MW to 11.1 MW (So the ratio is 11.1/3.715). Likewise, the reactive power of the whole system, active and reactive of each residential loads is raised with the same ratio. As well, the branches of the network is supposed to have been augmented which means that the parameters r and x of the branches are reduced. The ratio of this reduction is supposed to be 1.5. The voltage level of the system is raised to 20 kV and since by this voltage increase and practical conditions, we supposed that the thermal capacities of the branches are enhanced which are presented in Appendix (Table A1). The first bus of the network is considered as slack bus and we determined its voltage value to be constant at 1.03 per unit. Maximum permissible voltage deviation of buses is assumed to be 0.5 per unit (so $V_i^{\mathrm{Max}}$ and $V_i^{\mathrm{Min}}$ stated in equation (8) are 1.05 and 0.95 per unit, respectively). It is supposed that the BSSs are located in Buses 18, 22, 25, and 33 [18]. Due to the whole number of EVs to be Charged and the share of each BSS therefrom (if the whole number of EVs distributed uniformly among BSSs), we regulate the maximum permissible power consumption for each BSS (the value of $S_k^{\mathrm{BSS,Max}}$ in inequality (7) which is assumed to be equal for all BSSs), 2 MW as demonstrated in Table A1. Due to the peak active power of residential load curve (11.1 MW), We assumed the $P_t^{\mathrm{Max}}$ to be 10.8 MW. This value can be regulated by independent system operator (ISO) of the distribution system due to the system capabilities or by the aggregator of the BSSs in the area due to their goals and field studies. However, the program can admit the various amounts of maximum power -- even more than the peak residential load-- and similarly, the various amounts of EV numbers to be charged or the battery capacities of the EVs, as well.

### C. Results and Discussions

The results and outputs of the charging method is presented in this section.

To evaluate the performance of the evolutionary algorithm used in this paper, the program run for 20 times in which the number of total iterations in each time was 100. statistic results including objective function and timing is presented in Table I. The computational timings were measured on Intel® Core™ i7-4790 CPU at 3.6 GHz, 8-GB RAM, and 64-bit operating system.

TABLE I. Statistic performance of the applied evolutionary algorithm

| | Objective function | Timing |
|---|---|---|
| Best | 7067 | 13.94 |
| Worst | 7371 | 14.57 |
| Median | 7174.5 | 14.21 |
| Mean | 7231.6 | 14.25 |
| Standard Deviation | 107.3 | 0.18 |

The time slot duration is considered 15 minutes. So, we have 96 time slots for each day and night. The whole active power consumption of the system, equivalent to the active power extracted from the substation (bus numbered 1), is illustrated in Fig. 4. The figure depicts the consumption with or without the EV charging process. It shows that this charging strategy can makes the whole load curve smoother, make the cost of EV charging at its lowest value according to its optimal siting through off-peak period. As well, it fills the valley of load curve without huge spike in power changes of loading. Nevertheless, the small fluctuations at hedge of the curve get more frequently that may disturb the governors' performance of generators. Due to the fact that the BSSs can act even as storages, this phenomenon can be solved by load levelling characteristic of storage devices which can provide load-frequency control (LFC) in each level we would like.

To demonstrate the amount of EVs charging power consumption, Fig. 5 is provided. The figure shows that the whole charging period is not including all of the time slots within a day and night which can be referred to the maximum permissible loading we regulate or the electricity price. Total Apparent Power Consumption of the system which includes active power demand of the BSSs along with active and reactive power demand of the residential loads in the system is expressed in Fig. 6.

Power consumption values of the BSSs within the whole time slots are shown in figures numbered 7 to 10 respectively. Due to the third constraint stated in (7), the consumption value of each BSS is limited to its maximum value (2 MW). Optimal value of objective function which comprises EVs charging cost and energy loss cost of the system, becomes 7233$ which the shares of charging cost and energy loss are 6429.5$ and 803.5$, respectively. The energy loss contains the total loss of energy for the flowing of current caused by not only the charging process but also the residential demand of the system during the whole time slots of day and night. The energy loss in relation to the total energy demanded by the whole system becomes 3.1%.

Voltage profile of the system in format of maximum and minimum value of each of the bus voltages among time slots of the day, depicts in Fig. 11. The minimum magnitude of the voltage among all buses in whole time slots was recorded 0.962 per unit. The maximum loading of each branch (maximum apparent power flowing through the branch) along with the maximum permissible loading of the branch is illustrated in Fig. 12. Eventually, the dynamic electricity pricing within the whole time slots is depicted in Fig. 13. The fundamental pricing is also illustrated to simplify the comparative sight.

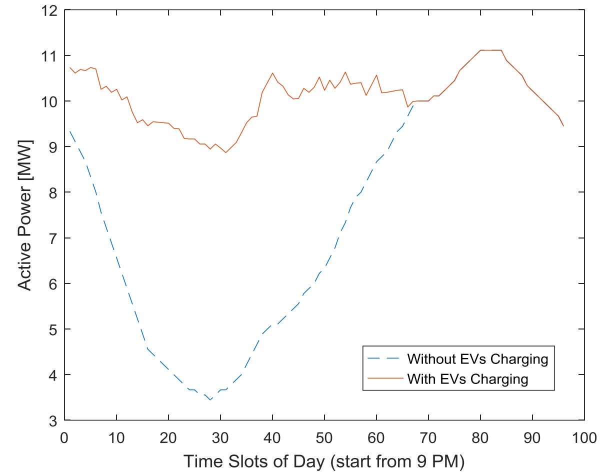


Fig. 4 Active Power Consumption of the System with & without EVs Charging

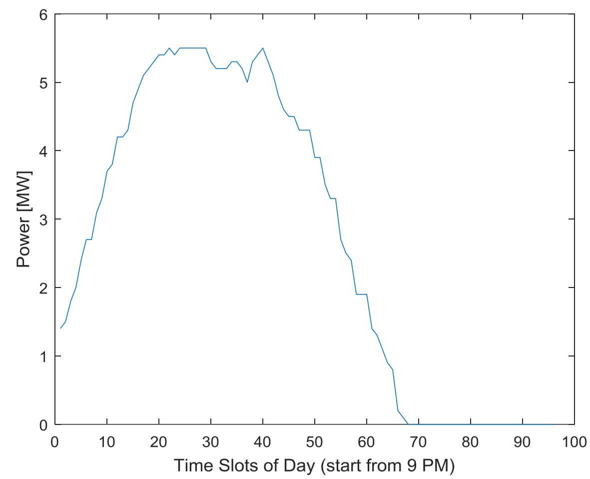


Fig. 5 Total Power Demand of BSSs

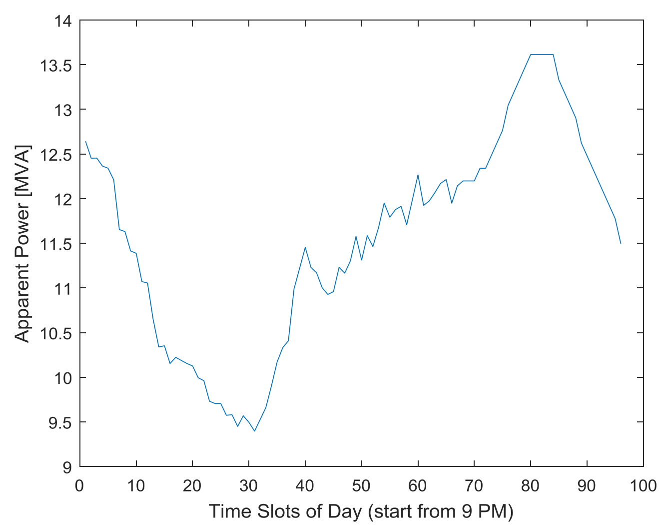


Fig. 6 Apparent Power Demand of the whole System [MVA]

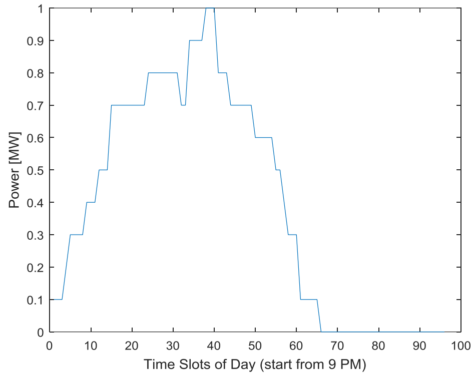


Fig. 7 Power Demand of BSS NO. 1 (Located in Bus 18)

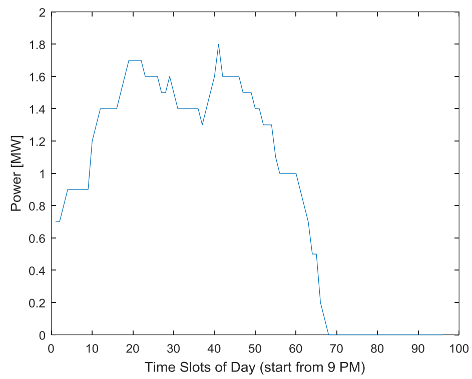


Fig. 8 Power Demand of BSS NO. 2 (Located in Bus 22)

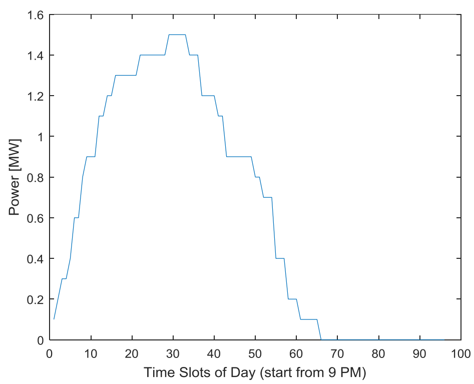


Fig. 9 Power Demand of BSS NO. 3 (Located in Bus 25)

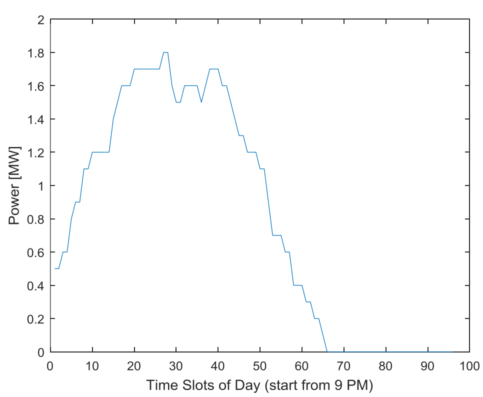


Fig. 10 Power Demand of BSS NO. 4 (Located in Bus 33)

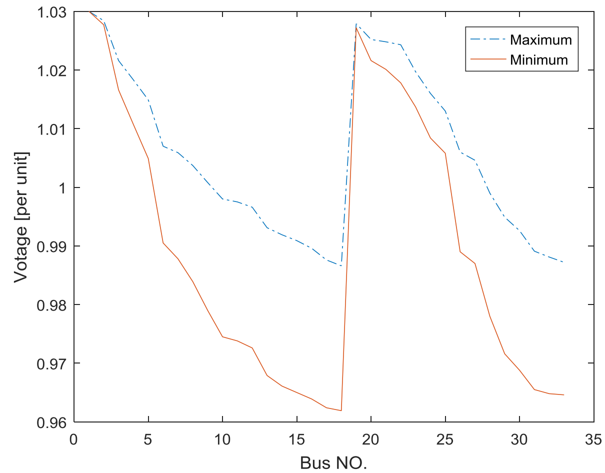


Fig. 11 Maximum and Minimum Voltage Profile of Buses among All Time Slots

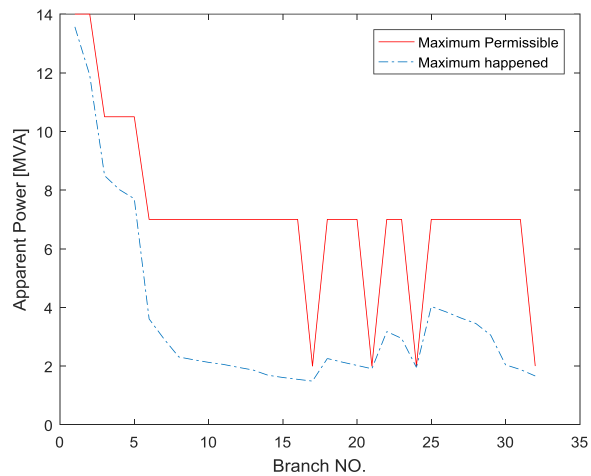


Fig. 12 Maximum permissible and Maximum Happened Flowing apparent power Through Branches among All Time Slots

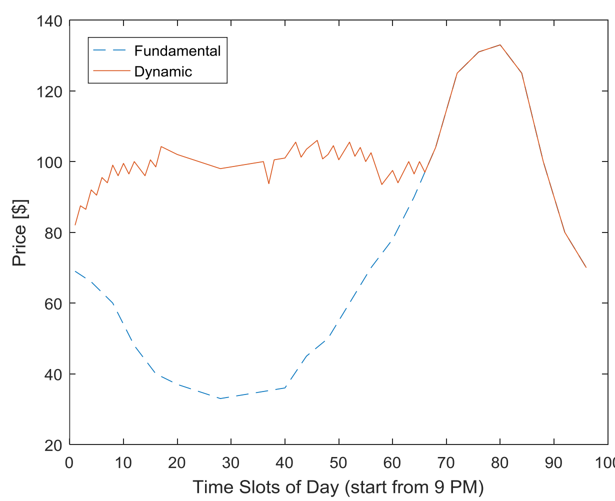


Fig. 13 Fundamental and Dynamic electricity Price

## VII. Conclusion

This paper presents an optimal charging schedule of BSSs based on the charging cost of EVs and energy loss of the distribution system considering network security. In order to approach the real conditions, we have simulated a dynamic electricity pricing related to power consumption of the EVs charging process. An evolutionary algorithm which is a modified hybrid form of GA and PSO, was exploited to find the best location and priority of EVs. A deterministic mathematical program has been achieved to find the least possible EVs charging cost for every decision variables vector of the optimization problem. In various cases, the results show that the aggregator of the area which is responsible for EVs charging operation and energy loss of the system, can change parameters in order to gain the optimal operation of the system in different conditions. The required power of the system is just provided through the substation. With presence of distributed generations and particularly renewable types of them, the performance of the system with BSSs is envisioned promising especially with the ability of BSSs to participate in the energy storing processes which is necessary for the local energy-load grids, microgrids, within a smart grid. This idea can be strengthened by applying the use of IoT along with the smart grid infrastructure which can facilitate the connectivity, mobility, gathering and storing of information, and so on.

## Appendix

TABLE A1. Thermal Capacity of Network Branches

| Sending Bus | Receiving bus | Branch NO. | Thermal Capacity (MVA) |
|---|---|---|---|
| 1 | 2 | 1 | 14 |
| 2 | 3 | 2 | 14 |
| 3 | 4 | 3 | 10.5 |
| 4 | 5 | 4 | 10.5 |
| 5 | 6 | 5 | 10.5 |
| 17 | 18 | 17 | 2 |
| 21 | 22 | 21 | 2 |
| 24 | 25 | 24 | 2 |
| 32 | 33 | 32 | 2 |
| Other Branches | | | 7 |

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